Closing the Loop in Feedback Driven Learning Environments Using Trust Decision Making and Utility Theory

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Abstract—Contemporary learning systems are an integration of learning resources with human interactions. To close the loop in feedback driven learning environments, the utility of learning objectives need to be measured. To this end, a comprehensive trust evaluation model for decision making is required to utilize feedback ratings along with other key parameters such as previous course result percentage, active participation and reputation of learners. This paper proposes a novel utility theory based trust evaluation model, wherein the utility of a learning objective is computed in terms of trust applicable to big datasets. The utility is computed by allowing users to weigh the course related attributes according to their preferences. The utility value facilitates learners to select trustworthy learning objectives and enables instructors to improve different aspects of learning objectives. In addition, a satisfaction index is proposed for the assessment of the usefulness of the computed utility value. The performance of the model is evaluated on a big data-set, which is collected from learners enrolled in different courses of a postgraduate degree program for the purposes of decision making. The results indicate that the proposed unique intelligent model is effective for dynamic and user-specified trust evaluations of learning objectives for the purposes of decision making.

Index Terms— Big data, decision making, educational cyber physical systems, feedback loop, learning systems, trust, unique environments, utility theory.

I. Introduction

Over the past decade, the developments of information and communication technologies have brought new opportunities in the domain of learning and teaching. The contemporary learning systems, which are an integration of learning resources with human interactions (human-in-the-loop cyber physical systems), are continuously evolving in the form of learning management systems (LMS), e-learning systems, and hybrid learning systems [1]–[4]. The course selection activity in these systems, based on ratings, is critical and untrustworthy. Recommendations, the trust values in learning systems, are typically computed on the basis of interaction history among human participants, which help to close the loop in learning systems [5], [6], [30]. The user's expectations of trust in learning systems typically affect their use and learning outcomes. Therefore, trust is considered to be a crucial need in order to create credible e-learning services [7].

The past literature [9] shows an uncertainty in regards to the trustworthiness of student assessments and hence the feedback ratings of a course evaluation may not truly represent the performance of instructors and quality of teaching. A solution to this uncertainty problem has been proposed by Mahmud and Usman in [9], through which the decision-makers can evaluate the trust of a learning objective on the basis of traditional average ratings in that study. However, the method does not consider the input from trustworthy learners as well as the previous result percentages of a learning objective as important trust antecedents. Trust evaluation in learning environments has two dimensions, namely, the trustworthiness of a learning objective and the trustworthiness of an instructor [7], [8]. In this paper, we have investigated the opinion of learners and queried if they trust learning objectives and instructors on the basis of previous feedback rating evaluations. Based upon this investigation, we proposed a more reliable trust evaluation model to facilitate instructors in order to find less focused areas of teachings.

The multi-aspect utility of learning objectives is computed using the feedback ratings which are submitted by previous learners. The method allows users (learners and instructors) to weigh the course related attributes according to their preferences; hence, supports the user-specific choice. Previous learners, who provide feedback ratings, may show a biased behavior, which may negatively affect the trust value. To avoid such biased feedback ratings, users are provided with the selection process in order to filter learners with biased and nonserious feedback. The outcome, because of its multi-aspect nature, can be taken as a decision to choose a specific learning objective from the perspective of a learner. Also, it can be interpreted as a decision about required changes in the course design from the perspective of an instructor. The preference weights by the decision-maker, produces a user specific trust value that cannot be achieved by computing the average of rating points. A satisfaction index has been proposed for the assessment of the validity of the model. The proposed model has been applied on real feedback rating data. The results indicate its usefulness in real world learning environments.

Decision making for big data-sets can pose a slew of issues because of high dimensionality, lack of heterogeneous structure, complexity, and unpredictable data features which almost always have differing levels of uncertainty. The uncertainty in data-sets will often be due to factors that can include absent values, errors in measurement, process change during data collection, and lack of appropriate monitoring of data measurement process. Additionally, such issues seriously affect the students' trust in selection of course (based on feedback ratings) in heterogeneous LMSs, e-learning systems, and hybrid learning systems. Therefore, the utility evaluation of learning objectives is appear to be one of the most influential way in decision making for course selection.

The main contributions of this paper are as follows: (i) a learning objective, trust evaluation model based on the weighted expected utility theory, is proposed that incorporates user preferred trust parameters, (ii) a satisfaction index is proposed for the assessment of validity of utility outcomes, (iii) the performance evaluation has been carried out on the dataset which is collected from an LMS that has been designed, developed, and deployed to gather feedback ratings for this study, and (iv) Some analysis is conducted to approve the effectiveness of the proposed approach. The rest of this paper is organized as follows: Section II describes the related work. The details of the proposed trust computation model are presented in Section III. The performance of the proposed model is evaluated in Section IV. Finally, Section V concludes the findings of this study.

II. Related Work

Trust is an imperative factor for the adoption of e-learning in both fully online and blended learning systems [10]. The evaluation of trust in network-based systems has been widely investigated in the literature. The efforts have been made in different contexts of trust, in which security mechanism-based trust, learning system characteristics and context, quality elearning services, identifying trust inducing factors, and exploring trustworthy learning paths have been research hotspots. A number of studies have been focused on security mechanism-based trust computation of learning systems by employing the policy, certificate, and reputation-based approaches [8], [11], [12]. A trust evaluation model for online learning, by integrating reputation and policies, was presented by Anwar *et al.* [8]. The study advocates the crux of trust lies in ensuring privacy preservation. The security and privacy related issues in distributed learning systems have been investigated by Xu and Korba [11]. Their trust model is based on the usage of public key cryptography for interactive learning environments. A hybrid trust evaluation model, which includes the functional trustworthiness along with technological security measures, was presented by Miguel *et al.* [12]. The researchers explored the satisfaction of integrity and authentication by employing digital certificates for secure e-assessment. Moreover, Elia *et al*., proposed a novel approach to analyse the learners' satisfaction level towards the course, by employing Big Data analysis [28]. The authors advocated the Big Data as a right paradigm for the processing of real time and large data sets regarding the Learner Satisfaction in Collaborating Learning environments. Moreover, the article presented a software artefact which incorporates the Big Data Learning Analytics concerning real-time insights of evaluation strategy of online courses. However, the proposed method lacks the consideration of learner preferences, regarding the course learning objectives, while evaluating the satisfaction level. These schemes have focused on the security of user credentials in learning systems. The trustworthiness of learning objectives is, however, not considered in these studies.

Another dimension of the research has been the investigation and analysis of the perception of users about the usage experience liable to characteristics and context of online learning systems. Pelet and Papadopoulou explored the importance of interface characteristics and use of colors in order to improve trust level [13]. The findings of the exploratory qualitative study demonstrate that the trust can be established and influenced by using appropriate colors of online interfaces. A study on trust in learning systems, from the perspective of major stakeholders (learners and instructors), was conducted by Jairak *et al.* [14]. The satisfaction of users on different learning environments was investigated. The findings of the study reveal that the blended learning systems are more trustworthy. These studies have formalized trust as ease-of-use aspect of learning systems and pressed the need for the investigation of trust with respect to the content (that is, learning objectives).

The review of the literature also illustrates that some studies have been focused on the quality of learning services in distributed systems [15], [16]. A trust management model, to ensure the provision of an e-learning service in cloud-based e-learning, has been presented by Tan *et al.* to evaluate the subjective and objective trusts of users [15]. The trust value represents overall capability of the system in order to perform tasks according to the requirements of users. Service-oriented architecture (SOA) is widely adopted in distributed learning systems due to its ability of loose coupling and reuse. Liu *et al.* presented an SOA-based model for trust evaluation [16]. The study was mainly focused on the evaluation of trust of education services. Although, these studies have explored the methods to evaluate the trustworthiness of learning services, none of them have evaluated the trustworthiness of learning objectives.

The identification of trust inducing factors has also been focused by some researchers. The learning experience can be enriched by integrating social media technology in learning management systems. Vassileva presented an idea of social learning technologies [17]. The work has been focused on the integration of existing and emerging web techniques (for example, ontologies and social tagging) into learning systems. An attempt has been made to address the challenge of integrating social and technical influences which affect the trustworthiness of online courses [18]. The key contribution of the study is investigation of twelve trust inducing factors from the existing literature. A trust model has been presented by

Wongse-ek *et al.* [19]. The model is intended to define the degree of trust of learners on teaching activities. The trust antecedents are highlighted in the study. These studies have highlighted factors which affect the trustworthiness of learning resources. However, no experiments have been carried out to validate the hypotheses postulated in these studies.

A trust model for open knowledge communities is designed by Yang *et al.* [20]. The resources and user trustworthiness, along with influencing factors, have been incorporated in the model. The trust of learning resources is evaluated by allowing users to score them directly and by considering user resource interaction frequencies. The challenge of identifying trustworthy collaborators and trustworthy learning resources is addressed by Yang *et al.* [21]. The authors proposed a trustworthy peer-to-peer social network for knowledge sharing communities. The works presented in these studies have been focused on trustworthiness of learning objectives, but these studies have overlooked the consideration of user preferences in the estimation of trust. A few studies in the literature have been focused on the identification of reliable peers and suitable learning resources by trustworthy learning paths [22], [23]. Carchiolo *et al.* defined trust as reliability of peers and the trustworthiness is associated with learning objectives in peer-to-peer (P2P) learning systems [22], [23]. A directed graph-based trust-aware framework has been designed. The trustworthiness of P2P or peer-to-resource (P2R) is represented by edges. A trustworthy resource is suggested by a trustworthy peer in the framework. Although the method computes trustworthiness of learning resources on the basis of trustworthy peers, it lacks the capability to facilitate users in order to evaluate trust on the basis of their own preferred trust attributes. Moreover, the users are not empowered to filter malicious feedback.

A trust model, as a solution to uncertainty problem, for the selection of learning objectives has been recently studied [9]. The trustworthiness of a learning objective is computed on feedback ratings. The model evaluates the utility by employing the traditional average computations. The decision makers are not able to evaluate learning objectives by considering the trustworthiness of learners. Moreover, the previous result percentage of a learning objective is ignored despite of its importance among learners. In another recent work, Matcha *et al*., examined the learning strategies with the temporal characteristics along with the investigations on their association with feedback [29]. The data was collected from flipped classroom activities. To detect the learning strategies, Clustering, sequence mining, and process mining were employed. The positive association of feedback with learning performance was analysed by using inferential statistics. However, the collection of feedback is independent of several key parameters of course learning.

A Few recent studies illustrate efforts for course recommendation in various personalized learning scenarios [30], [31]. Ibrahim *et al*. developed a framework of an ontology-based hybrid-filtering system [30]. The study introduces a novel method to personalise the course recommendations. The system integrated the information from several sources based on hierarchical ontology similarity, hence, resulted a personalized course recommendation that matches the needs of students. Nevertheless, the feedback information about the course effectiveness can be integrated to improve the aspects associated with recommender systems. An optional course recommendation system based on score prediction is designed by Huang *et al*. [31]. A novel cross-user-domain collaborative filtering (CUDCF) algorithm is presented to predict result of the optional course. The score prediction has been carried out by employing course score distribution of past students enrolled in same course. The authors investigated that the students with similar scores in prior courses, generally acquire same result in the subsequent courses. The highest predicted scored optional courses are recommended to students. Moreover, the effectiveness of proposed method has been carried out by experiments. Conversely, the proposed system recommends courses considering only the similarity of students. Some important factors, i.e. course feedback, user preferences of trust factors, for the selection of courses has not been considered.

A number of above-cited trust evaluation models have considered security assurance as a guarantee for trustworthiness of a learning system. Moreover, the trustworthiness of learning objectives and instructors or peers has been computed on the basis of interaction with the system and peer collaboration history. The review of the literature shows that no attention has been paid to compute learning objective utility in the context of trust, which can serve for multiple purposes. The learning objective trustworthiness and active participation of a learner can affect the reputation of an instructor. Moreover, none of the past studies have paid attention towards user preferences in order to find the utility of learning objectives. Thus, a comprehensive utility-based trust evaluation system is required to evaluate the trust of a learning objective. In this study, we have, therefore, proposed a user specified trust evaluation model by extending the utility theory to trustworthiness problem in learning systems.

III. Utility Theory-Based Trust Computation Model

A utility theory based trust computation model has been proposed which aims to facilitate user (learner) in decision making of course selection based on feedback ratings. The main objective of this work is to enable users to weigh the course related attributes according to their preferences and produce a result based on user-specific choice.

A. Utility of Learning objectives

The utility of a learning objective, in the proposed method, is computed by considering the learning objective (course) evaluation ratings and user preference weights, as discussed in Subsections III-A1 and III-A2, respectively.

1) Utility Evaluation Data: The proposed model is based on multiple constituent elements which contribute to the utility of a learning objective with respect to a learner. These elements have different evaluation scale ranges. We normalize them, on a scale ranging from 0 to 1, to compute the utility of learning objectives. The structure of the constituent elements is summarized below.

Ratings: The learners rate learning objectives on the basis of their learning experience. The learning objectives are rated against some typical evaluation factors which are mentioned in Table 1, under the category of ratings. Each of the factors are rated by following a typical 5 point Likert scale, where 1 denotes the lowest and 5 represents the best value. The aggregated value for a course utility is graded on a scale ranging from 0 to 1.

Suppose a group of n learners rate a learning objective against q rating parameters. Each learner individually evaluates the q parameters by using 5 point Likert scale. The rating assessments, provided by the past learners, are computed as a single utility value for new learners with the consideration of their chosen priorities. Upon obtaining the ratings of the q parameters from the n learners, a $n \times q$ rating matrix R can be obtained as

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1q} \\ r_{21} & r_{22} & \cdots & r_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nq} \end{bmatrix}. \quad (1)$$

Trustworthy Learners: The rating values are essentially selected from trustworthy learners in order to avoid malicious evaluation. The selection of trustworthy learners deals with two aspects: first, the active participation or engagement of a learner in the learning activities and second, the individual score of a learner given by an instructor on the basis of his/her performance in a particular learning objective. The active participation results are collected by keeping track of interaction activities of a learner.

We consider the following aspects in order to collect interaction data from our developed LMS. (i) The participation of a learner in group discussions, (ii) the total time spent in learning activities on LMS by a learner, (iii) the participation of a learner in rating of learning objectives, and (iv) the participation of a learner in rating of announcements. We consider aspects (i) to (iv) as features F_i of learner participation, where i = 4 and F_i contributes to the total participation value $R \in [0,5]$. The features F_i are evaluated as follows:

- $F_1 = \frac{C_s}{C_{max}} \times 5$, where C_s is the total comments posted by a learner s in a group, C_{max} is the maximum number of posts by any learner.
- $F_2 = \frac{T_s}{T_{max}} \times 5$, where T_s is the total time spent by the learner s during the learning duration and T_{max} is the maximum time spent by any learner.
- $F_3 = p_s$, where p_s represents the participation of the learner s in rating of a learning objective at the time of course completion.
- $F_4 = \frac{A_s}{A_{max}} \times 5$, where A_s is the number of announcements which are rated by the learner s and A is the total count of announcements in the selected learning objective.

The total participation value is computed as

$$R_1 = \sum_{i=1}^{4} \frac{F_i}{4}, \quad (2)$$

where F denotes the participation value of feature i. The computation of R_1 depends on the performance of learners during learning duration. The learning performance of learners is evaluated by an instructor on the basis of some defined metrics r, such as quizzes, assignments, midterm, and final term scores.

The resultant grade of an individual learner is computed as

$$R_2 = \frac{\sum_{i=1}^{t} r_i}{T}, \quad (3)$$

where T denotes total marks from which the grade would be computed and t is the total number of metrics.

R_3 is the percentage of attendance which indicates the regularity of the learner in attending lectures delivered by the instructor.

Result percentage: We use the overall result percentage of a group of learners who experienced the learning objective in its previous offering. This factor is considered due to the fact that learners usually seem to be more interested in grade scores. In this study, the course result percentage, represented in Table I, serves as the possibility of having same result score. Let p_i be the result percentage obtained by learner i and let n represent the total number of learners. Then,

$$P = \frac{\sum_{i=1}^{n} p_i}{n}, \quad (4)$$

where $P \in [0,100]$. The summary of the utility evaluation constituent elements and their scales is provided in Table I. It is pertinent to observe that the utility evaluation does not encounter cold start and sparse data. The data collection for a particular learning objective occurs if that learning objective is registered by the learner. The learner does not need the previous history to submit his/her feedback. If the previous feedback ratings are available, then those could be utilized with the new data for decision making, otherwise only the new data is considered for decision making. Furthermore, the rating values for feedback parameters range among 1-5 (refer to Table I). Hence, if a learner inputs a response, it could never be zero. Therefore, it is highly unlikely to obtain sparse data values. Moreover, if a learner does not participate actively in the learning activities, then he/she can be excluded from the decision making process considering him/her untrustworthy learner. This eliminates the chances of sparse data.

2) User Preferences: The literature shows that the feedback ratings have been employed for course evaluation, but the past studies have not incorporated user preferences to determine the utility of learning objectives. Our proposed method enables users to apply preference weights on rating attributes to compute expected utility. Moreover, the users are empowered to weigh the expected utility outcomes according to their preferences.

B. Trust Evaluation

1) Expected Utility of Learning objectives: The trust evaluation model employs utility theory [24] to compute the expected benefits of learners and expected demand of change for instructors. The expected utility is computed for decisionmakers on the basis of learning experience of previous good learners. The perceived learning achievements and satisfaction primarily depends on evaluation procedures and interactions between learners and instructors. We consider three categories related to teaching skills and course evaluation, namely, (i) Course Learning, (ii) Instructor Responsiveness, and (iii) Grading Criteria, as main rating constituent factors of learning objectives (Table I). Each category includes multiple parameters. These parameters are selected from the course evaluation questionnaire which is currently being employed for course evaluation in the Department of Computer Sciences, <anonymous> University. However, the proposed utility evaluation model can also be adopted for other course evaluation rating parameters involved in a learning system.

TABLE I: Utility Evaluation Contributing Elements And Their Scales

Category	Data Source	Description	Scale
		Ratings	
Course Learning	Q_1	Fully functional course	1-5
	Q_2	Well organized	1-5
	Q_3	Generates project ideas	1-5
	Q_4	Content and assignment compatibility	1-5
Instructor responsiveness	Q_5	Instructor encourages independent thinking	1-5
	Q_6	Instructor regularity	1-5
	Q_7	Lecture delivery	1-5
	Q_8	Instructor is fair in grading	1-5
	Q_9	Instructor availability	1-5
Grading criteria	Q_{10}	Graded assignments cause understanding of subject	1-5
	Q_{11}	Satisfaction with evaluation rules	1-5
	Q_{12}	Learner participation	1-5
		Trustworthy Learners	
Trustworthy Learners	R_1	Participation	1-5
	R_2	Individual grade of a learner in previous offering	0-100
	R_3	Attendance percentage	0-100
		Result Percentage	
Percentage	P	Course result percentage	0-100

The utility model is defined as $< L,S,U,R,P >$, where L denotes a learning objective, S represents a set of learners, U is the learning objective utility, R illustrates the union of the values of the rating parameters of three categories, namely, Course Learning (CL), Instructor Responsiveness (IR), and Grading Criteria (GC) of trust parameters; $R = \bigcup_{j=1}^{3} R_j$, where $R_1 = \{a_1,a_2,...,a_x\}$, $R_2 = \{b_1,b_2,...,b_y\}$, and $R_3 = \{c_1,c_2,...,c_z\}$, and P denotes the learning objective result percentage. The number of parameters in each category, CL, IR, and GC, are denoted by x, y and z, respectively. The set represents CL parameters set having $x = 4$ for a_x and defined as $Q_1 - Q_4$ in Table I. The notation R_2 denotes the set of parameters of IR, having $y = 5$ for b_y and defined as $Q_5 - Q_9$ in Table I, and R_3 represents the set of parameters for GC, having $z = 3$ for c_z and described as $Q_{10} - Q_{12}$ in Table I. As an initial step, we compute the mean value for each parameter and each category. The mean value q_i is the average of parameters a_i, b_i, and c_i, and is defined as

$$q_i = \frac{\sum_{s=1}^{n} d_s}{n}, \tag{5}$$

where d_s denotes the value of parameter question q_i rated by learner s, and n is the total number of learners who have participated to rate q_i. The mean M_{R_j} of ratings for each category R_j, is defined as

$$M_{R_j} = \frac{\sum_{i=1}^{k} q_i}{k}, \tag{6}$$

where k denotes the number of parameters included in category R_j. The utility U is weighted average of a learning objective L and defined as

$$U = \sum_{i=1}^{m} \frac{M_{R_j} \times w_i}{\sum_{i=1}^{m} w_i}, \tag{7}$$

where w_i represents the weightage assigned to the calculated mean value M_{R_j} and m is the total number of rating categories. For simplicity, weight-based normalization implies that $\sum_{i=1}^{m} w_i = 1$, hence Equation 7 can be written as

$$U = \sum_{i=1}^{m} (M_{R_j} \times w_i). \tag{8}$$

The computation result from Equation 8 is utility $U \in [0,5]$, which specifies the utility of a learning objective with respect to user preferences. We normalize the value of U, such that $U^N \in [0,1]$, using a linear stretch method [25] as follows:

$$U^N = ts_1 + \frac{(ts_n - ts_1)(U - ps_1)}{ps_n - ps_1}, \quad (9)$$

where U^N represents the normalized utility value. ps and ts denote the primary and target scales, respectively. In this study, the primary scale (ps^1, ps_n), has values [1,5] and the target scale (ts_1, ts_n) has values [0,1]. We have $ts_1 = 0$ and $ts_n = 1$, thus, U^N can be derived from Equation 9 as follows:

$$U^N = \frac{U - ps_1}{ps_n - ps_1}. \quad (10)$$

2) Weighted Expected Utility Based Trust Computation: The Weighted Expected Utility (WEU) computation results serve as trust value ν for the user. The user is empowered to weigh the expected utility outcomes according to his/her preferences by employing the valuation function given by the weighted expected utility. The trust value is computed by using the valuation function given below.

$$\nu = \frac{\lambda w_1 u(l_1) + (1-\lambda) w_2 u(l_2)}{\lambda w_1 + (1-\lambda) w_2}, \quad (11)$$

where $u(\cdot)$ is the utility of a learning objective with expected outcomes l_1 and l_2, λ is the probability, and w is the preference weight assigned to utility l_1 or l_2. The utility values U, from Equations 8 and 10, are employed as $u(l_1)$ and $u(l_2)$ can be computed as $1-u(l_1)$. The result percentage P of a learning objective is normalized to $[0,1]$ and taken as probability λ of obtaining the expected outcome l_1. We consider default values for preference weights w_1 and w_2 as 0.5. However, the user defined weights can also be employed as per user requirements.

3) Algorithm and Analysis: The proposed algorithm consists of two phases, namely, initialization and main procedure. The computation of average values for all parameters, included in categories CL, IR, and GC, is performed in the initialization procedure. This phase accepts the rating values, provided by learners, as input. Hence, the learners are required to rate a learning resource in order to initiate the procedure. The value of mean for each of the rating category is computed by using Equation 6 at the end of the initialization procedure.

ALGORITHM 1: Trust Evaluation.

Phase 1: Initialization Procedure Input: Ratings d by n trustworthy learners. for $1 \le i \le x$ **do**

$q_i \leftarrow \frac{\sum_{i=1}^{n} d_i}{n}$

end

for $1 \le j \le 3$ do

$M_{Rj} \leftarrow \sum_{ki=1} \overline{k\ q_i}$ end Output:

List of means M_R

Phase 2: Main Procedure

Input: Weights w_1, w_2, w_3, and a list of means M_R.

$\mu \leftarrow 0$ for $1 \le j \le m$

do $\mu \leftarrow M_{Rj} + \mu$ end

$\mu \leftarrow \frac{\mu}{m}$

for $1 \le i \le m$ do

$U \leftarrow \sum_{mi=1} (M_{Rj} \times w_i)$

end

$U^N \leftarrow \frac{U - ps_1}{ps_n - ps_1}$

$u(l_1) \leftarrow U^N$

$u(l_2) \leftarrow 1 - U^N$

$\nu \leftarrow \frac{\lambda w_1 u(l_1) + (1-\lambda) w_2 u(l_2)}{\lambda w_1 + (1-\lambda) w_2}$

Output: Trust value ν

The main procedure computes the utility U of learning objectives on the basis of mean value which is derived from the first phase. The preference weights and probability values serve as input values for this phase. The preference weights are applied by employing Equation 8 and the computation results are then normalized by Equation 10. The weighted expected utility valuation function, defined in Equation 11, is employed to compute the user specific trust value. The pseudo-code of the proposed utility evaluation method is given in Algorithm [1] .

The time complexity of the proposed algorithm is O(k+n) for Phase 1 as the average of rating parameters takes the constant time for k number of parameters evaluated by n learners. The computation of utility of learning objective in Phase 2 takes the constant time for normalization and weighted expected utility involving m number of categories. Hence, the time complexity is O(m). Therefore, the overall time complexity of algorithm is O((k+n)+m), but as the first term dominates the other, it is stated as O(k + n). The correctness and termination of the algorithm can also be argued in terms of two phases of the algorithm. The initialization phase requires rating for parameter qi (in this case 1 ≤ i ≤ n but in a different setting it can have any upper bound) by n trustworthy learners along with categories Rj (in this case 1 ≤ j ≤ 3). Steps 1 and 2 in the initialization phase compute the average and means of qi and Rj, respectively. The correctness of both these steps can be proved by induction on i and j, respectively.

The main procedure has six steps. Step 2, among them, involves a loop involving *m* rating values. The correctness of this step can be proved simply by induction on *m*. Rest of the Main procedure steps from 3 to 6 just involve simple assignment statements which become the inputs of next steps or statements and their correctness can be established through Equations 8, 10, and 11 to compute the trust value ν.

TABLE II: Satisfaction Index Threshold

Value	Threshold
Strongly acceptable/Excellent	$0.8 \le \delta_i$
Acceptable	$0.7 \le \delta_i < 0.8$
Slightly acceptable	$0.6 \le \delta_i < 0.7$

Not acceptable	$\delta_i < 0.6$

The non-termination of an algorithm can be due to loops which are not properly guarded, but in this case, there are three loops in the algorithm at Steps 1 and 2 of the initialization procedure and Step 2 of the main procedure. All these loops are determinate loops with well-defined terminating criteria and loop variants. These variants increase strictly in each iteration of these loops to reach the terminating condition of the loop in its final iteration. To be precise, the strictly increasing loop variant is i in all the loops with upper bounds n, k and m in the first, second, and third loop of the algorithm. Therefore, the algorithm will eventually terminate when these loops terminate and doing the remaining assignments to give the desired output.

C. Satisfaction Index

The satisfaction index is presented to judge the acceptance of results by a decision-maker. Siskos et al. and Huang et al. proposed a customer satisfaction index for group decisions by analyzing the difference between group decisions and individual preferences [26], [27]. In this study, a satisfaction index is presented in order to show the strength of utility results for an individual decision maker where the assignment of preference weights is analyzed. Table II defines the thresholds for the acceptance of the satisfaction level. These thresholds are based on the scale associated with the Masters degree program result grades. The greater the satisfaction index value, the more satisfactory the decision maker, which is the conceptual interpretation in terms of percentage. Note that the value of utility U is based on a group decision (ratings) by previous learners in previous offerings of a learning objective.

The instructors and new learners, who are interested in the computation of the utility of a learning objective, are taken as decision-makers in this study. The importance weights, selected by a decision maker, are efficacy values according to the user. The satisfaction level δ is defined as

$$\delta_i = 1 - \frac{1}{m}\sum_{i=1}^{m} w_i \nu, \qquad (12)$$

where for i $(1 \le i \le m)$, δ_i represents the satisfaction index for an individual decision-maker regarding selected weight combinations w_1, w_2, w_3.

The notation m denotes the total number of categories and ν is the value of utility derived from Equations 8 and 10. The greater value of δ_i yields that the computed utility is more satisfactory for a decision maker.

The overall satisfaction index is given by

$$\delta = \frac{\sum_{i=1}^{c} \delta_i}{c}, \qquad (13)$$

where c denotes the total weight assignment cases, that is, all possible weight combinations w_1, w_2, w_3, which satisfy the condition $\sum_{i=1}^{m} w_i = 1$, are considered.

D. Numerical Example

Let ten learners rate a learning objective L, which they experienced in a blended learning system. The set of calculated mean value against each of the parameter q_i is R = $\{4,3,2,2.5,4.5,3.5,3,3,4,2.5,4\}$, where $\{4,3,2,2.5\} \in R_1$, $\{4.5,3.5,3,3,3\} \in R_2$, and $\{4,2.5,4\} \in R_3$ having $x = 4$, $y = 5$, and $z = 3$ for the number of parameters in R_1, R_2 and R_3, respectively. On the basis of these values and using Equation 5, the calculated mean values M_{R1}, M_{R2}, and M_{R3} are 2.875, 3.4, and 3.5, respectively.

Let the importance weights by two new learners S_1 and S_2 as $(1,0,0)$ and $(0.4,0.3,0.3)$, respectively. The utility U of the learning objective, based on the specified weights, for S_1 and S_2 are shown in Table 3. The results for U in Table III shows that the learning objective is more beneficial for S_2. According to our proposed method, the user is able to consider the importance of utility outcomes, that is, we have $u(l_1) = U^N$ from Equations 8 and 10. This implies $1 - U^N = 1 - u(l_1) = u(l_2)$. The user can weigh the $u(l_1)$ and $u(l_2)$. Let $(0.5,0.5)$ and $(0.2,0.8)$ denote the weights selected by S_1 and S_2, respectively, and 60% be the course result percentage which is experienced by past learners in a previous offering of the learning objective. The trust value is computed by employing weighted expected utility ν defined in Equation 11. The satisfaction index δ_i and overall satisfaction value δ is calculated by employing Equations 12 and 13, respectively. The values of ν in Table IV indicate that the learning objective is trustworthy for S_1. However, the learner S_2 gets a lower trust value on the basis of his/her concerns for $u(l_2)$.

The satisfaction index is greater than 80% in each case; hence, shows the effectiveness of the utility results for the selection of a learning objective, specific to decision-makers S_1 and S_2. On the other hand, if the satisfaction value is lower than 0.6, then the utility value would not be satisfactory for a learner. To evaluate the performance of the proposed model, the effect of standard deviation on the utility is examined.

Table V shows the standard deviation values which are calculated for four learning objectives, namely, C_1, C_2, C_3, and C_4. The standard deviation values of CL, IR, and GR for C_1 to C_4 are plotted in Fig.1. Fig. 1 also depicts the plot of utility values against 66 different weight combinations for w_i, w_2, and w_3 such that $\sum_{i=1}^{3} w_i = 1$. The valid weight combination is denoted by W_i. Let $W = \{0,0.1,0.2,0.3,\ldots,1\}$ be the set of all valid values for w_i, then $W_i = \{(w_1,w_2,w_3) | w_1 + w_2 + w_3 = 1\}$.

The utility evaluation results for different standard deviations, shown in Table V, illustrate the inverse relationship of utility and standard deviation of feedback ratings (Fig. 1), as C_4 with the highest standard deviation value (0.577) shows the lowest utility. The standard deviation specifies the

TABLE III: Utility Evaluation Example

	(w_1, w_2, w_3)	U	U^N
S_1	(1, 0, 0)	2.875	0.575
S_2	(0.4, 0.3, 0.3)	3.218	0.6436

TABLE IV: User Specific Trust Evaluation Example

	$u(l_1)$	λ	w_1, w_2	ν	δ_i	δ
S_1	0.575	0.6	0.5, 0.5	0.515	0.82833	0.823222
S_2	0.6436	0.6	0.2, 0.8	0.435	0.855	0.856313

TABLE V: Feedback Rating Standard Deviation

	CL	IR	GC	Ave. St. Deviation
C_1	0.144	0.163	0	0.102
C_2	0.276	0.163	0.157	0.198
C_3	0.5	0.596	0.314	0.47
C_4	0.745	0.421	0.566	0.577

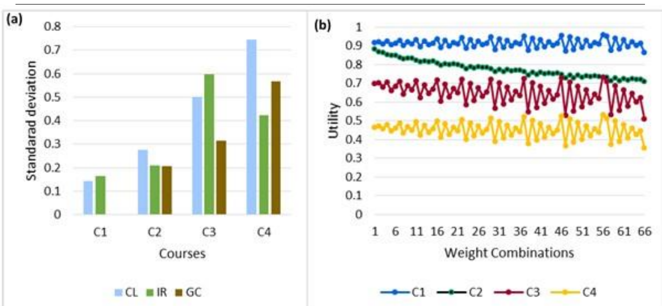

Fig. 1: (a) Standard deviation, and (b) Utility values against different weight combinations w_1, w_2, w_3.

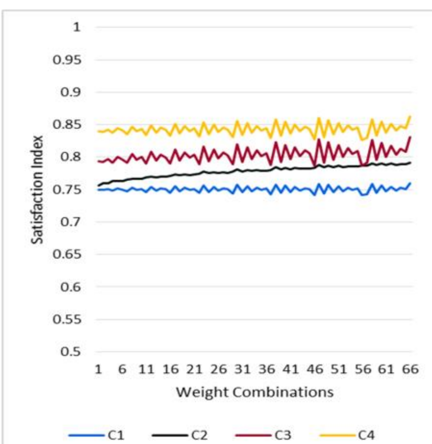

Fig. 2: Satisfaction index.

difference of attributes (CL, IR, GC) from their combine mean value. This implies that the standard deviation measures the certain deviation of expected utility for a learning objective. Hence, the increase in the value of standard deviation restricts a decision-maker to select a learning objective.

The satisfaction index δ_i is computed using Equation 12. The satisfaction index is calculated against each utility computed for C_1, C_2, C_3, and C_4 and presented in Fig. 2. Each of the satisfaction level outcomes is greater than 75%, which demonstrates the acceptance level of results.

TABLE VI: Sample Size and Characteristics of Participants

Learning objective	Registered students			Semester
	Male	Female	Total	
WS	4	4	8	1st
HII	8	11	19	1st & 3rd
IVP	9	9	18	3rd & 5th
Total	21	24	45	–

IV. Performance Analysis

A. Experiment Setup

A distributed LMS system was implemented to gather data of the previous experience of course learning by learners and monitoring of activities which are performed by learners to evaluate the utility of learning objectives. The visual Studio 2015, object oriented programming language (C#), and relational database management system (SQL Server 2012) were utilized to build the Restful Web service. The system was developed with two user interfaces, namely, Instructor Panel and Learner Panel (Fig. 3). The instructors were provided with the functionalities to upload the details of learning objectives, showing helping materials, assignment tasks, and discussion topics. The learners, on the other hand, were able to view and download contents, take part in discussions, and provide feedback ratings. The history of the activities performed by learners while working with the system was maintained to select the trustworthy learners, as elucidated in Section III. The system was empowered to compute the interaction data automatically against each action of the learner. Moreover, the system was configured to collect ratings against three rating categories for learning experience, as discussed in Table I. However, the students were restricted to submit the feedback for a particular learning objective until the end of the semester (learning duration) which is upheld by the implementation of a clock counter. When the particular learning duration was found to be ending, the learners were provided with the links by the system, to submit feedback ratings only once about their learning experience. The data privacy issues were considered by anonymizing all user data and storing data only for research purposes. The user who participated in the data collection process also filled the data collection consent form containing a statement of data protection. The rating values of trustworthy learners along with an overall academic performance in previous course offerings serve as the independent variables. The user specific utility of a learning objective is considered as a dependent variable for the sake of analysis.

1) Study Participants: The dataset for experiments is collected from a set of students who are enrolled in MS degree program in the [department name], [university name]. We selected three learning objectives, namely, Web Services

(WS), Human and Information Interaction (HII), and Information Visualization and Presentation (IVP), offered in the Spring 2017 semester. The set of students belong to the first, third, and fifth semesters of the degree programme. Table VI summarizes the details of the registered students in the Spring 2017 semester.

2) Data Collection Technique: The existing course evaluation questionnaire was made available online through our developed LMS, namely, QLMS to collect data. The students performed learning activities throughout the semester. The students evaluated their respective registered courses at the end of the semester. The evaluations of the courses by the students

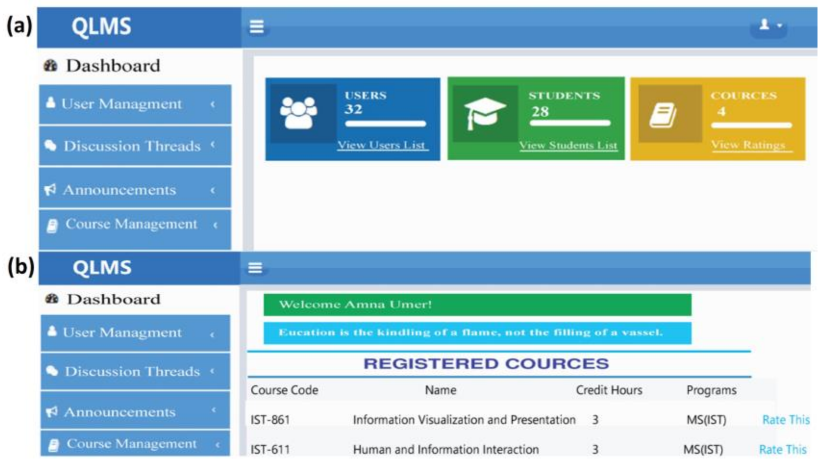

Fig. 3: (a) Instructor panel and (b) Learner panel.

TABLE VII: Categorization of Questions

Q. No.	Criteria	Description
1–4	Course learning	These questions target the content organization and content valuability of the learning objective.
5–9	Instructor responsiveness	The attributes related to IR focus on the availability, communication, and teaching style of an instructor.
10–12	Grading criteria	The fair grading and evaluation rules are emphasized in GC.

were focused on three categories of evaluation questions, namely, CL, IR, and GC (Table VII).

3) Questionnaire Structure: The questionnaire is adopted from the course evaluation procedure, which is manually practiced in the CS department. The existing course evaluation standard consists of sixteen questions regarding course effectiveness, integrity of an instructor, and teaching qualities. These attributes are evaluated by students using a Likert scale. We modified the existing questionnaire to avoid the ambiguity, redundancy, and to maintain consistency among evaluation attributes. Hence, the number of attributes to be evaluated is reduced to twelve questions. These twelve questions target certain aspects of a learning objective including Course Learning (CL), Instructor Responsiveness (IR), and Grading Criteria (GC).

The questionnaire includes closed-ended questions which accept a numeric value, based on the star rating scale against each of the targeted attributes. CL targets the content organization and content valuability of a learning objective. The questions included in IR emphasizes on the punctuality of an instructor, availability, expertise, and the teaching effectiveness of a learning objective. The student grading, decisions about the mark distributions, and evaluations of quizzes, assignments, and exams are considered as focal points of GC. Table VII provides the description of the questions with their related criteria.

B. Results and Analysis

The valid feedback rests on the assumption that the values of IR affect the values of CL and GC, as student learning and

TABLE VIII: Regression Model Summary for CL (Dependent Variable) and IR (Predictor)

Model	R	Rsquared	Adjusted R-squared	Std. error of estimate	Observations
1	0.793	0.628	0.566	0.535	8
2	0.638	0.407	0.372	0.738	19
3	0.792	0.628	0.605	0.543	18

TABLE IX: Regression Model Summary for GC (Dependent Variable) and IR (Predictor)

Model	R	Rsquared	Adjusted R-squared	Std. error of estimate	Observations
1	0.691	0.477	0.389	0.682	8
2	0.598	0.358	0.321	0.821	19
3	0.679	0.461	0.428	0.676	18

TABLE X: Regression Model Summary for GC (Dependent Variable) and CL (Predictor)

Model	R	Rsquared	Adjusted R-squared	Std. error of estimate	Observations
1	0.571	0.326	0.213	0.774	8
2	0.608	0.370	0.333	0.813	19
3	0.733	0.536	0.507	0.627	18

grades are also dependent on the performance of instructors. Similarly, the ratings of GC can also be influenced by CL, as the student achievements depend on their learning. Therefore, we observe the variability in CL which is caused by IR, and variability in GC which is caused by CL and IR by examining that how well regression models fit the data. Tables VIII, IX, and X show the summaries of the regression models for the variability effects of the evaluation criteria variables, namely, CL, IR, and GC on each other. We perform such analysis for three groups of data, namely, WS, HII, and IVP. We are interested in column “R-Squared”, which is the coefficient of determination and it shows the variance in CL and GC (Tables VIII, IX, and X). Table VIII shows that IR causes 62.8% of variability of CL, for Groups 1 and 3, but 40.7% for Group 2. Hence, we acknowledge the fact that the CL ratings can be moderately affected by the values of IR.

The line fit plots with y (CL) and predicted y are shown in Fig. 4. All three plots (Fig. 4) illustrate that predicted y has linear relationship with variable x (IR) and the Y data points deviate from the predicted Y at some data points. This supports the argument of a moderate variability in the CL ratings due to the IR ratings. Table IX shows a summary of regression models of the cause and effect relationship between IR and GC. It is evident from results that IR causes less than 50% of variability of GC for all three groups. Hence, we state that the GC ratings can be slightly affected by the values of IR. The line fit plots with y (GC) and predicted y are shown in Fig. 5. The linear relationships between y and variable x (IR) have been observed in all three plots, but Y and predicted Y CL causes less than 55% of variability of GC for all three differentiate in most of the cases. Table X shows that the groups. Hence, it can be admitted that CL ratings can be moderately affected by the values of IR. The line fit plots with y (GC) and predicted y are shown in Fig. 6. All three plots illustrate that predicted y has linear relationship with variable x (CL). CL causes low variability in GC ratings. Therefore, a large number of values of Y and predicted Y are different.

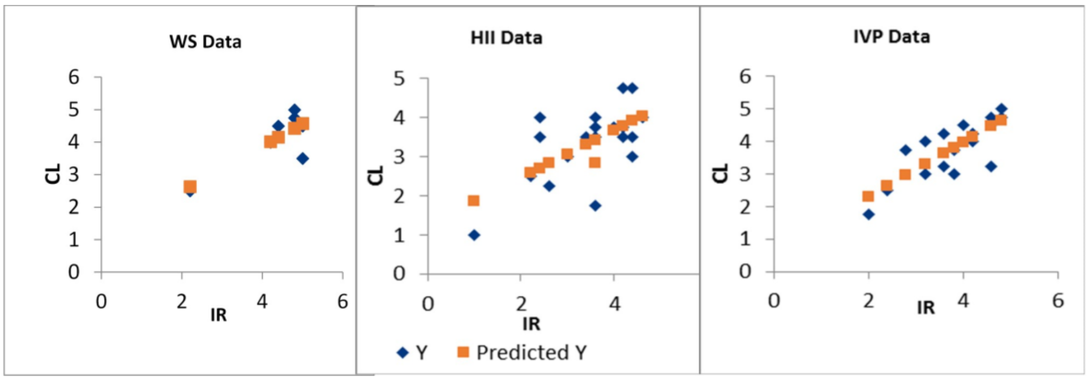

Fig. 4: Line fit plots for IR and CL.

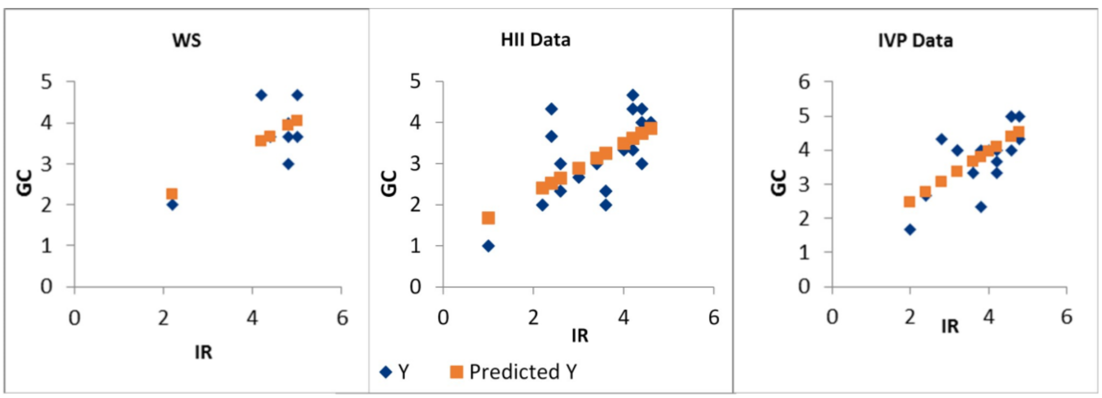

Fig. 5: Line fit plots for IR and GC.

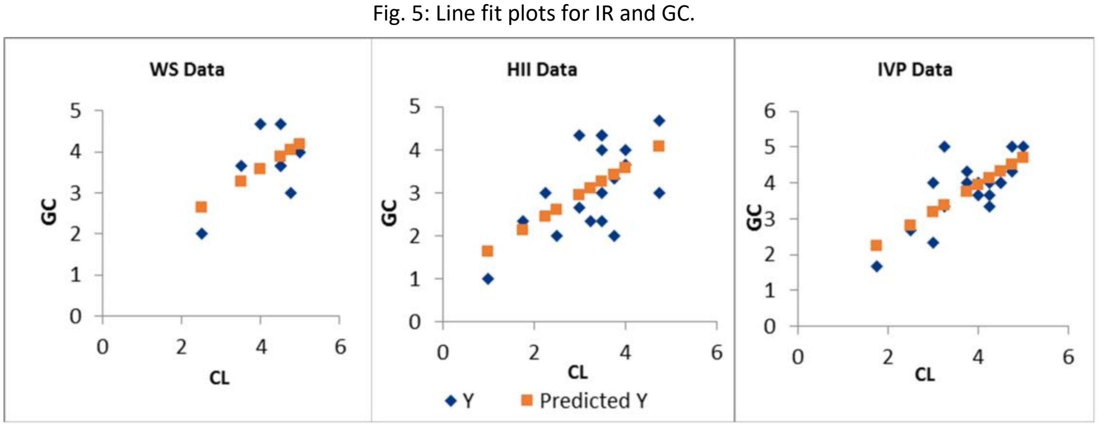

Fig. 6: Line fit plots for CL and GC.

The variability effect results of all three categories, namely, CL, IR, and GC, on each other show that the categories have low cause and effect relationship. Hence, it can be interpreted that the utility evaluation, based on user preferences, produces a user specific and independent trust value. Fig. 7 shows the effect of R-Squared values on the utility values. The results show that the learning objectives having low R-Squared values possess low utility value. This implies that the high R-Squared values show that the learning objective contents are well structured and well delivered.

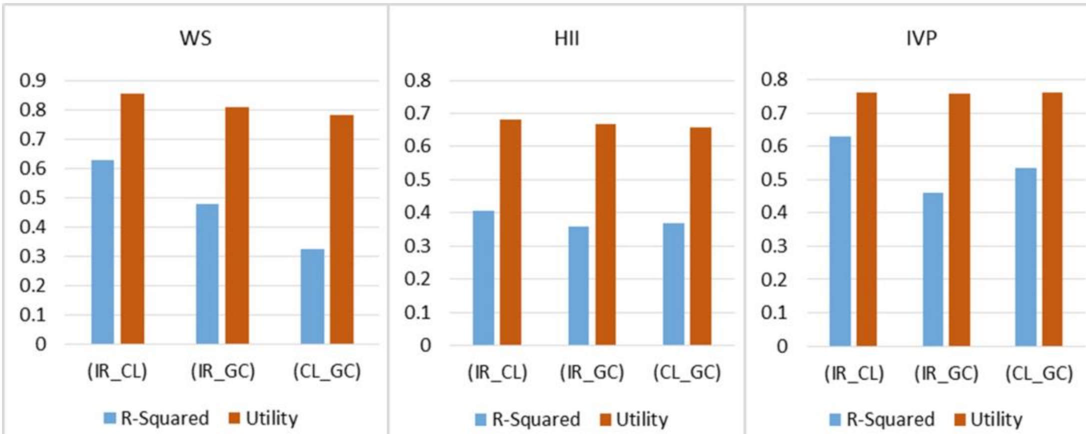

Fig. 7: R-squared vs. utility.

TABLE XI: Utility Computation Based on Trustworthy Learners

Probability	Weights	Trustworthy learners		All learners	
λ	(w_1,w_2,w_3)	ν	δ_i	ν	δ_i
0.8	(1,0,0)	0.75	0.75	0.58	0.81
0.7	(1,0,0)	0.67	0.78	0.55	0.82
0.6	(1,0,0)	0.58	0.81	0.53	0.82
0.8	(0,1,0)	0.78	0.74	0.60	0.82
0.7	(0,1,0)	0.68	0.77	0.56	0.81
0.6	(0,1,0)	0.59	0.80	0.53	0.82
0.8	(0,0,1)	0.72	0.76	0.56	0.81
0.7	(0,0,1)	0.65	0.78	0.54	0.82
0.6	(0,0,1)	0.57	0.81	0.52	0.83

Let us consider three values for probability λ as 0.6, 0.7, and 0.8 and set the values of w_1 and w_2 as 0.5 for computing WEU. However, w_1 and w_2 can vary as per the choice of users. The computation of ν is performed by employing Equation 11. The utility is computed using the weights $(1,0,0)$, $(0,1,0)$, and $(0,0,1)$. Fig. 8 shows the difference of utility evaluations which are computed on the basis of the values of ratings which are submitted by trustworthy learners and ratings submitted by all learners including untrustworthy learners. The ratings by the trustworthy learners increased the utility value up to 0.8, but this value remained below 0.6 because of the malicious ratings. The satisfaction index δ_i for each computed ν for all learners is shown in Table XI, where each value is greater than 75% which shows the validity of results.

The utility or the trust values of the learning objective with respect to the instructor is illustrated in Fig. 9. The calculations are performed using 0.5 value for w_1 and w_2 with three different values of λ to analyze the effect of variation in λ. Two cases, Case 1 and Case 2, of the average learning object ratings are considered having values 0.80 and 0.53, respectively. For both cases, the respective instructor may be interested in finding out the best and worst aspects of learning objective teaching by assigning the preference weights to the categories of interest (CL, IR, GC). For example, weights $(1,0,0)$ show that the instructor is interested in CL category and wants to explore the response of learners with respect to course learning in previous offerings.

TABLE XII: Utility with Respect to Instructor

Case	λ	Weights (w_1,w_2,w_3)	ν
Case 1	0.80	(1,0,0)	0.68
		(0,1,0)	0.71
		(0,0,1)	0.65
Case 2		(1,0,0)	0.44
		(0,1,0)	0.8
		(0,0,1)	0.32
Case 1	0.70	(1,0,0)	0.62
		(0,1,0)	0.64
		(0,0,1)	0.60
Case 2		(1,0,0)	0.46
		(0,1,0)	0.7
		(0,0,1)	0.38
Case 1	0.60	(1,0,0)	0.56
		(0,1,0)	0.57
		(0,0,1)	0.55
Case 2		(1,0,0)	0.48
		(0,1,0)	0.6
		(0,0,1)	0.44

Considering λ = 0.8, the results shown in Table XII and Fig. 9 indicate that the GC, grading criteria, category is least valued by the learners in Case 1. In Case 2, IR, instructor responsiveness, was highly appreciated by the learners, but the learners seemed to be unhappy with CL and GC. The instructor needs to revise the strategies regarding CL and GC. Similarly, for other two values of the results are varied accordingly.

The proposed method enables learners to interpret these utility results (Table XII) with respect to their interest. For example, for Case 2, the learners who consider IR more important than CL and GC, get the result 0.8, 0.7, and 0.6 depending on λ, but the learners who are more interested in CL or GC may not be recommended to register this course. The average rating values, which are usually computed in most of the learning systems, fail to depict such multi-aspect, noteworthy, and highly required information about the utility of learning objectives.

V. Conclusion

The goal of this research was to design and develop a multiaspect model for dynamic evaluation of learning objectives for learners, that is, the key components of the learning management cyber-physical systems, in an internet-based or hybrid learning system. We focused on developing a method for the selection of suitable learning objectives in a specific learning context and environment. The core of the suitable selection is dynamic evaluation, which incorporates the preferred attributes of a learning objective according to the choice of a particular learner through closing the learning feedback loop. Furthermore, the utility of a learning objective, from the perspective of instructors, identifies weak aspects regarding course learning, instructor responsiveness and grading criteria according to the choice of learners. The analysis is performed to examine the effects of standard deviations and variability relationships among course learning, instructor responsiveness, and grading criteria on the utility values. The calculations for standard deviation illustrate the inverse relationship with utility. The fitness of regression models has shown that the variables course learning, instructor responsiveness, and grading criteria have low cause and effect relationship. Moreover, the learning objectives having low R-Squared values possess low utility value. The utility evaluation results depict the multi-aspect information about the learning objective trust in real-world settings.

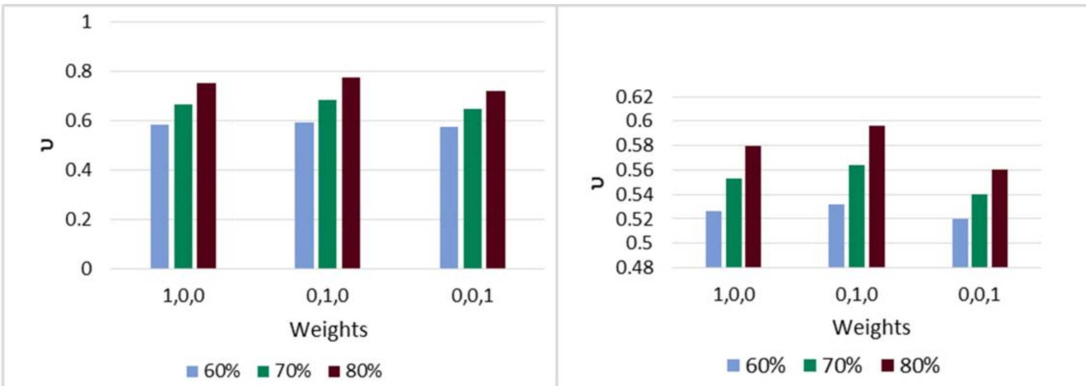

Fig. 8: (a) Utility computation based on the ratings by trustworthy learners and (b) utility computation based on the ratings by all learners.

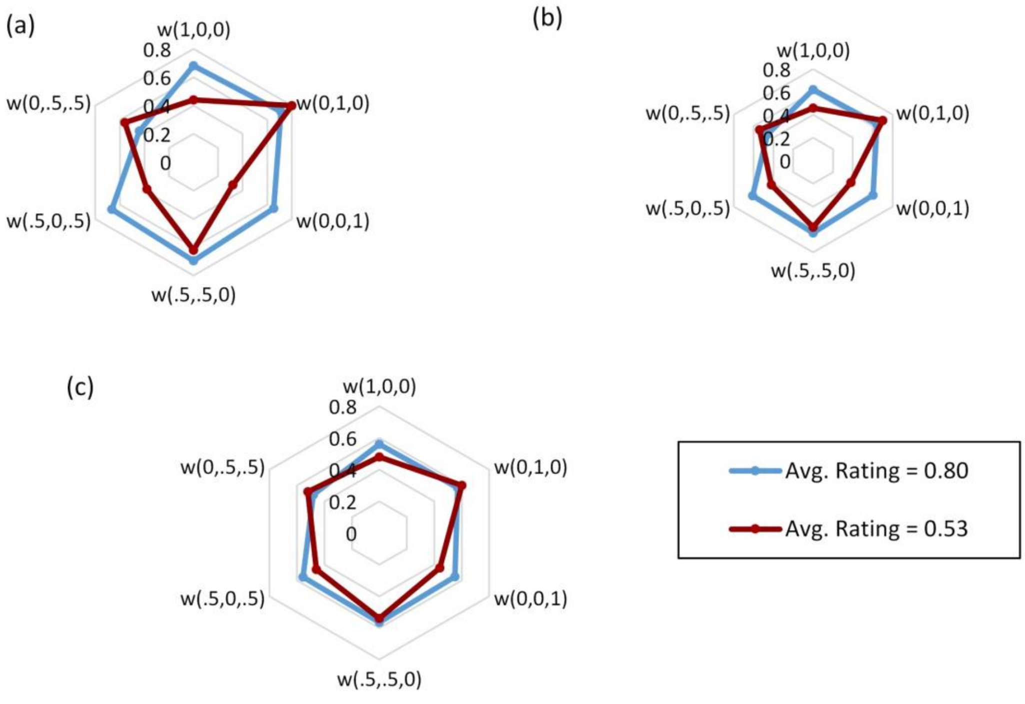

Fig. 9: Utility computation from the perspective of an instructor.

This work is based on the quantitative data. The inclusion of qualitative feedbacks (open-ended questions) and sentiment analysis in our proposed trust evaluation model may be explored as a future work of this study. Moreover, the proposed model can also be extended by including the trust reducing factors along with the trust building factors. The trust reducing factors incorporate ratings for negative questions such as avoiding responsibility and biasness in grading in the learning feedback loop process of the educational and learning management cyber-physical systems.

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